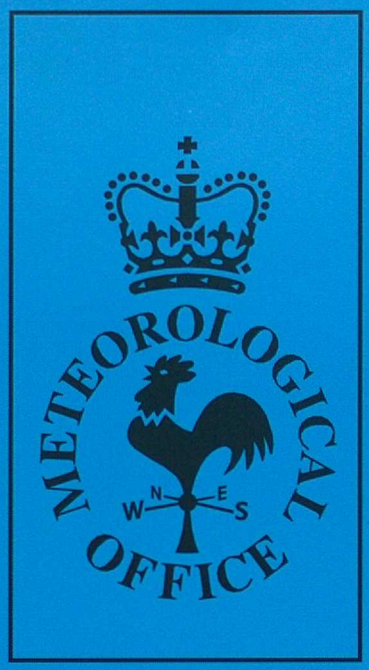

Forecasting Research

Forecasting Research Division
Technical Report No. 231

Satellite-based techniques for estimating tropical convective precipitation

by

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December 1997

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Abstract

Radar rainfall estimatesare currently assimilated into the UK Met Office Mesoscale Model via a Latent Heat Nudging scheme. This assimilation can lead to both a reduction in the spin up time of the Model, and an improvement in rainfall analyses and forecasts. It is believed that benefits may also be gained in the Global Model, given observations of rainfall on a global scale. In order to achieve such observational coverage, it is necessary to consider satellite data.

The purpose of this report is to provide a broad review of the many satellite rainfall algorithms available, and to make recommendations on which approaches are most suitable. The report is exclusively concerned with estimating convective precipitation in the tropics at all longitudes, since it is for this that we expect to obtain the clearest improvement in the Model.

The results of assimilation studies undertaken by researchers at several centres are summarised, and satellite rainfall algorithms categorised and described. The respective benefits and shortcomings of algorithms are assessed, drawing on the results of previous intercomparison studies. Selection of the most appropriate algorithm is discussed, and a way forward outlined.

1. Introduction.

When water vapour condenses in clouds latent heat is released into the atmosphere. Since the storage capacity of liquid water within a cloud is relatively small (Holton 1979, chapter 12), the majority of condensed water will form precipitation. Therefore, precipitation rate may be used as a measure of the amount of condensation which in turn approximates the vertically integrated latent heating rate. This latent heating is an important input in attempting to understand the dynamics of the atmosphere.

In the tropics, convection is the dominant precipitation mechanism, and tropical convective precipitation has been identified as one of the major forcing mechanisms of the global circulation. Conventional observations in the tropics are sparse, and in this region the skill of the Unified Model (UM) is poorest. For these reasons, it has been proposed to derive global tropical precipitation estimates from satellite data, and assimilate these estimates into the UM as latent heating through a latent heat nudging (LHN) scheme (Jones and MacPherson 1997).

The requirement has beeen advanced for satellite-based estimates of surface rainfall throughout the tropics at all longitudes. The estimates must be suitable for operational implementation in near-real time at 3-hour intervals and at a spatial resolution of 60km.

The aim of this report is to investigate the options and outline the preferred method for deriving precipitation estimates suitable for operational assimilation, but this is not a straightforward task and it is not at all clear which data source and algorithm would yield the most accurate rain estimate. This point is underlined by the variety of rainfall algorithms evident in recent research on rainfall assimilation. We shall attempt to identify the 'best' approach based on the nature of the UM, the quality, coverage, and resolution of the estimate we might obtain, the feasibility of obtaining the necessary data in a timely and reliable way, and the practicality of processing this data.

The report first outlines experiments elsewhere (at ECMWF and in the USA) on the assimilation of tropical rainfall data. Algorithms for estimating tropical convective rainfall are then reviewed in two groups: Vis/IR and passive microwave. The use of active microwave sensors (space-borne radar) is not considered here because the object of the report is to seek methods that may be applied operationally in the very near future. Finally, the choice of algorithm is discussed, taking account of practical constraints as well as of reported performance. An incremental approach is recommended, first establishing an end-to-end processing system based on a simple IR thresholding scheme, to allow the observational and model fields to be compared, their gross characteristics to be establshed and, if justified, some impact experiments to be performed. The rainfall estimation algorithm can then be refined (or even completely changed) according to the results obtained.

2. Recent work on the assimilation of rainfall rates

Currently, no operational model assimilates global tropical rainfall observations on a routine basis. However, various studies have been performed using the European Centre for Medium Range Weather Forecasting (ECMWF) model (Heckley et.al., 1989), the Florida State University (FSU) model (Krishnamurti et.al., 1995), and the National Center for Environmental Prediction (NCEP) model (Treadon, 1995, 1996). Brief discussions of these studies follow, and a summary of these is given in Table 1.

2.1. The ECMWF model

Heckley et al, (1989) used data from the High Resolution Infrared Radiation Sounder (HIRS) instrument flown onboard the NOAA-9 and NOAA-10 polar orbiters. The assimilation was performed at each of the main synoptic hours (00,06,12,18Z) taking all passes from the 2 satellites which fell within ±3 hours of data time. Typically between 5 and 10 orbits were available resulting in few data voids across the global tropics. The first 12 HIRS channels were regressed to outgoing longwave radiation (OLR) using a relation previously calculated by inputting a number of known atmospheric profiles to a forward radiative transfer model. Heckley et al., note previous work done with the ECMWF model by Puri (1987) in stating that OLR in itself does not provide a sufficiently good measure of precipitation. Thus, these OLR are then converted to brightness temperature (T_b), and the HIRS spots collected into boxes of 7*7. The fractional coverage of cold cloud (FCCC) is then calculated for each box by counting the number of spots with T_b less than 235K, giving FCCC on a 2.5°*2.5° grid. They then perform a Cressman analysis on both the FCCC and the observation times. This processing fills in gaps between close orbits, smooths the data, and produces a field of confidence weights based on data density which are then scaled for asynopticity and latitude. The weights become zero poleward of 35°, and can only reach their maximum value equatorward of 25°. Finally, precipitation rates are calculated from the simple equation:

$$precipitation\ rate = 3 * FCCC\ (mm/hr)$$

which is the same equation used to derive monthly GOES Precipitation Index (GPI) values for the Global Precipitation Climatology Project (GPCP). The field of weights is used to smoothly integrate the model and satellite-derived values of precipitation before input to the Kuo convection scheme (Kuo, 1965). It was noted that in areas where the model analysis has a stable flow such as in the equatorial Atlantic or over the tropical continents at night, even heavy diagnosed precipitation is not always converted to convective heating by the Kuo scheme. A data assimilation experiment was run with data from 1/2/87 to 8/2/87 which falls within the second active period of the 1987 Australian monsoon, and at a time when additional soundings and SYNOP data were available from the Australian Monsoon Experiment (AMEX), the Equatorial Mesoscale Experiment (EMEX), and the Stratosphere-Troposphere Exchange Project (STEP). Seven analyses and 1 forecast, both with and without assimilation of satellite-derived precipitation rates, were objectively validated against radiosonde measurements. Significant impact and modest improvement was evident in analyses and forecast below 150hPa, although some problems seemed to occur above 100hPa. It was noted that the precipitation estimates used for this study were

of a very crude nature, and were very heavily filtered in the initialization.

2.2. The FSU model

Krishnamurti et al., (1995) used a method called physical initialization to assimilate 'observed' rain rate into the Florida State University (FSU) model. The global tropical rain rates were derived from a mixed algorithm which incorporates polar orbiter satellite infrared (IR) and microwave (MW) measurements as well as raingauge data (Gairola and Krishnamurti 1992). Olson et.al. (1990), Kummerow and Giglio (1994), and Spencer (1993) each developed a rain retrieval algorithm based on SSM/I data. Each of these was considered by Krishnamurti, and used to estimate the daily rainfall amount for 6th September 1987 over all oceanic tropical regions (30°N to 30°S). The methods gave quite different results, the correlation between any 2 out of the 3 estimates being of the order of 0.6. Averaging spatially over the data area gave values ranging from 1.95mm/day to 3.92mm/day. These differing rain estimates were found to invoke significantly different responses from the model in producing medium range forecasts. By consideration of the most appropriate spatial resolution for high resolution global model integrations, and the constraints placed upon rainfall estimates by global hydrology, it was decided to use the algorithm of Olson as the SSM/I component of the mixed algorithm. The mixed algorithm uses an SSM/I-sharpened OLR-derived rainrate as a first-guess across the global tropics. Prior to operational running, a regression relation is formed between the Laplacian of OLR-derived rain rates and a collocated dataset of the Laplacian of SSM/I-derived estimates. The data on which this regression was based spanned the globe between 10°N and 10°S at 1° latitude/longitude intervals over a 10 day period. Then, in 'real-time' mode, global tropical rain estimates are derived from the OLR data and the Laplacian of these rain estimates formed. The regression relation is then invoked and the Poisson equation solved to yield the 'SSM/I' or 'sharpened OLR' rainrate estimate covering the entire tropical belt between 30°N and 30°S. To augment this first-guess field, rain rates retrieved by the Olson algorithm from current SSM/I data over the ocean, and rain amounts measured by gauges on land are incorporated into the rainfall analysis. The 'observed' rainfall is collected in 6-hour bins at a spatial resolution of a spectral transform grid square (T106~100km) for assimilation via the physical initialization procedure. Krishnamurti applied physical initialization in the FSU model at T106 to data throughout October 1991 and reports that the procedure demonstrated bettter skill than the various operational centres in both nowcasting and forecasting to the order of 1 day.

2.3. The NCEP T62 model

Treadon (1995, 1996) used the physical initialization scheme of Krishnamurti to assimilate rainrate into the National Meteorological Center Global Data Assimilation System (NMC GDAS). However, Treadon obtained his rain estimates solely from geostationary IR data by applying a slightly modified GPI algorithm called the Morrissey-Greene GPI or, simply, the MG-GPI (Morrissey and Greene 1993). Hourly GPI rainfall analyses on a 1°*1° lat/long grid between 40°N and 40°S started to become available on a quasi-operational basis at NMC in Spring 1994. The satellites providing this data during Treadon's study were Meteosat-3, Meteosat-4, GOES-7, and GMS. Treadon recognises that the GPI was originally calibrated using data from the Global Atlantic Tropical Experiment (GATE), but cites Arkin and Xie (1994) and Xie and Arkin (1994) as indicative that the

GPI provides reasonable rainfall estimates throughout the tropics albeit with some regional and seasonal biases. It was noted that the rain data between 50E and 90E was often of questionable value. This was due to the use of extreme scan angle data from Meteosat-4 and GMS since Insat data was not operationally available. Further, only data between 30°N and 30°S were assimilated since the GPI technique tends to over-estimate rain coverage and intensity at larger zenith angles. It was clear from Krishnamurti's work that the impact of physical initialization upon the model forecast was sensitive to the imposed rainfall analysis. Significant differences were found when each of the three different SSM/I algorithms were applied to the same data. Kasahara et.al. (1994) argued that the qualitative information of satellite rain estimates is valuable whereas the quantitative details are less reliable, and thus applied modifications to the satellite-derived rain. In agreement with Kasahara, Treadon believes that consistency between the space-time characteristics of the model and observed rain is paramount. To investigate this consistency, a 20-day mean of daily rain rates between 30°N and 30°S on the T62 grid (~200km resolution in tropics) was derived using the GPI, and the results compared to GDAS-produced rates. It was found that the GPI gave higher rates with larger standard deviations about the mean. Work by Morrissey and Greene (1993) suggest that the GPI tends to under-estimate light amounts and over-estimate heavy amounts of precipitation, and this could contribute to the larger deviations found by Treadon. Morrissey and Greene proposed a bias correction to the GPI, which later became known as the MG-GPI algorithm. Applying the MG-GPI to the 20-day dataset resulted in rain rates closer in mean and deviation to those that the GDAS-Medium Range Forecast (GDAS-MRF) naturally produces. Thus, in this study, the GPI product was preprocessed to the MG-GPI values.

Two experiments were run using the T62 resolution GDAS-MRF. The first covered the period from 31/5/94 to 4/6/94 and involved running a GDAS with rain rates assimilated alongside a control GDAS which did not assimilate rain rates. Forecasts out to 4 days were made from each of the days' 00 UTC analyses. These forecasts were then verified against GPI rain rates and correlation coefficients calculated using all data lying between 30°N and 30°S. The initialized forcasts were significantly better at all forecast times, and in fact, the 4 day forecast from the initialized GDAS showed equal or greater skill when compared to each of the non-initialized forecasts from 0 through to 4 days. The second experiment extended over a longer time period and again consisted of a control and a physically initialized run. 5 day forecasts were made from each 00 UTC analyses from 15/8/94 to 3/9/94. Correlation coefficients and Equitable Threat Scores (ETS) based on daily precipitation totals were calculated for both runs, and the initialized nowcast and 1 day forecast found to be superior. The control run and the initialized run gave comparable results for forecast days 2 through 5.

2.4. The NCEP T126 model

Following these positive results with the T62 GDAS, Treadon went on to perform studies with the higher resolution T126 GDAS of the National Center for Environmental Prediction (NCEP, formerly NMC). The T126 model has an effective resolution of around 100km in the tropics. Since Krishnamurti found that the impact of physical initialization increased with increased resolution, it was hoped that this would also be the case for the

NCEP model. As before, precipitation data was derived from the MG-GPI. The study period ran from 20/5/95 to 25/6/95. Unfortunately, during this time, no GOES-8 GPI data was available, and thus only GOES-7, Meteosat-5, and GMS were available to cover the global tropics. As before, this meant using data of questionable quality from extreme scan angles. In the previous study, better results were found using 3-hourly running averages of MG-GPI with the T62 model, although little effect was evident at T126 resolution. The GPI product was available from GOES-7 and Meteosat-5 half-hourly, and from the GMS every hour. It was decided to have no temporal smoothing of this data. This precipitation data was assimilated into the T126 GDAS during the 6 hour forecasts linking successive GDAS analyses from 20/5/95 to 25/6/95. 5-day forecasts were made from each 00 UTC analysis from 21/5/95 to 19/6/95. A control analysis-forecast cycle with no assimilation of precipitation data was run in parallel, and the whole experiment repeated with the T62 model in order to assess the sensitivity of physical initialization to resolution. The resulting analyses and forecasts were objectively compared over all longitudes from 30°N to 30°S. A cost function can be used as an indication of how accurate an analysis is with respect to observations. Cost functions for several fields averaged over 20 analyses were calculated for both initialized and control systems at both T62 and T126 resolutions. The physically initialized run showed significantly better fits to the observations in most cases. However, surprisingly, the moisture field at T126 had a larger cost function than the control. It was suggested that this may be due to the fact that the reverse cumulus algorithm perturbs moisture alone in order to achieve a match between the model and MG-GPI rain, and therefore that too much of the burden in the initialization is placed on the moisture field. The precipitation forecasts for 1 through 4 days from the initialized GDAS were found to be consistently as good as, or better than, the control forecasts. It was noted that the T126 physical initialization performs better over sea points whereas at T62 superior performance is found over land points. No explanation is offered as to why this may be the case. As expected, in agreement with the findings of Krishnamurti, the improvement in precipitation forecast scores is greater at the higher T126 resolution. Although these results show an overall positive impact when rain rates are assimilated, Treadon notes some inconsistencies. The divergent wind forecasts, particularly in the tropics, rapidly depart from the physically initialized analyses. Further, the initial stages of a forecast briefly spin up from a physically initialized analysis, whereas the operational control exhibits spin down. These seem to suggest that the imposed rainfall rates are at odds with the rainfall climatology of the model. It is suggested that a benefit may be found from the formal development of a bias correction scheme between MRF and GPI (or some other satellite rain product) rain rate estimates. Also, the assimilation scheme does not incorporate any information about the error characteristics of the GPI data and the model. In an attempt to alleviate the introduction of the most damaging errors, the initialization is only performed when and where certain conditions are met eg. the initialization is not performed for rain amounts less than 5 mm day^{-1}. Despite the considerable variation in GPI availability throughout the study period, the physical initialization procedure was able to utilise the information within the GPI to positive effect in both analysis and forecast fields of the global NCEP model.

The above studies are primarily concerned with the problem of assimilating rainfall estimates into a global model, and demonstrating that such an assimilation has a positive impact. Less emphasis is placed upon the derivation of the rain amount from the raw satellite data which forms the input to the assimilation. Each author does however

acknowledge the significance of the characteristics of the rain estimate on the results of the assimilation. Spatial sampling, spatial and temporal resolution, and the error characteristics of the rain estimate all have a bearing on how successfully the data can be assimilated into a numerical model. Due to practical considerations of data availability, volume, and processing complexity, decisions for an operational system may be based on reasons of expediency as well as on scientific virtue.

3. Satellite rain estimation algorithms

In discussing methods of rainfall estimation, we are concerned here solely with tropical convective systems. Unless otherwise stated, the methods described and the comments on their suitability will be relevant to tropical convective rainfall. Since the convective regime accounts for around 70% of tropical rainfall (Jones and MacPherson, 1997), and most of the work involving satellite techniques has been geared toward this regime, most of the material referenced can be interpreted in a similar manner.

3.1. Visible and infrared techniques

The goal of improving rainfall estimates from spaceborne sensors has been pursued for more than 20 years. As early as 1973 there was sufficient interest and activity in this area to warrant a review paper based on conferences of the previous year (Martin and Scherer, 1973). At this time, work was almost exclusively based upon measurements made in the visible (Vis) and infrared (IR) regions of the electromagnetic spectrum. The earliest studies were exploratory in nature, attempting to show some relationship between satellite-measured IR temperature and Vis brightness and ground station observations of precipitation. Radok (1966) found heavy rainfall in Indochina to be related to minima occurring a few hours later in the intensity of 8-12 micron window radiation observed from TIROS III. Lethbridge (1967) found that a decrease in 8-12 micron window radiation, and an increase in the 0.55-0.75 micron visible channel of TIROS IV individually correlated with precipitation occurring a number of hours later. Using both IR and Vis together gave the best results, with the probability of rainfall occurring 3 hours later ranging from 5% for high temperatures and dark scenes, to 75% for low temperatures and bright scenes. In other words, it would appear that colder, brighter clouds are more likely to precipitate, and to produce heavier precipitation, than warmer, darker cloud. Since brightness is a measure of optical depth, and therefore of thickness, and since in the tropopause there exists an almost universal lapse rate of temperature with height, we can equivalently say that brighter and colder clouds are thicker and higher, and therefore more likely to precipitate.

From a cloud physics perspective, Mason (1971) states that the relative importance of condensation, Bergeron-Findeisen, coalescence, accretion, and Langmuir chain reaction processes is largely a function of cloud thickness, cloud top temperature, and cloud base temperature. These macroscopic properties of the cloud, together with the updraft velocity, largely determine precipitation intensity. Subsequent observational findings (Sikdar, 1972; Griffith and Woodley, 1975; Reynolds and Vonder Haar, 1975) support the assumption that regions of rainfall tend to be correlated with bright, cold clouds, and although not well understood, this correlation remains the basis of many contemporary algorithms.

The problem of how to manipulate the indirect information supplied by IR/Vis measurements of cloud to yield rainfall estimates has been approached in a number of ways. In reviews of the subject, Barret and Martin (1981), and later, Kidder and Vonder Haar (1995) chose to subdivide these approaches into cloud indexing, life history, bispectral, and cloud model techniques. Although considered, thresholding techniques are not assigned a category of their own in these reviews. Thresholding techniques do not readily fit into any of these categories, and are of sufficient value to warrant separate discussion as a class in their own right. It should be noted that although it is convenient to partition algorithms in this way, divisions can be somewhat arbitrary and algorithms can often have aspects of more than one approach.

3.1.1. Cloud indexing

Principle

These techniques involve the classification of a satellite image (usually Vis) into cloud type. The fractional area of coverage for each cloud type is then calculated for grid boxes at the desired resolution. A fixed effective rainrate for each cloud type incorporates the probability of that cloud type producing precipitation. The contributions for each fractional coverage multiplied by the effective rainrate are summed for each of the grid boxes to give a rainfall estimate at each box. This is best summarised by the equation:

$$R=\Sigma_i r f_i$$

where R is the rainfall in a particular area, r_i is the effective rainrate assigned to cloud type i, and f_i is the fraction of the area covered with cloud type i.

Initial work

Barrett (1970) pioneered this method using daily nephanalyses from NOAA's predecessor, the Environmental Science Service Administration (ESSA). He used 8 cloud types in estimating monthly rainfall over the ocean. Follansbee (1973) streamlined the method of Barrett to produce daily estimates over a larger area from satellite photographs. He used only 3 cloud types, concentrating on the main rain-producing clouds. Kilonsky and Ramage (1976) developed a method of identifying "highly reflective clouds" (HRCs) from Vis images. From once-daily mosaics they produced monthly rainfall estimates by simply counting the number of days a location was covered by HRCs.

Drawbacks

Although some success has been found with all of these algorithms, they do share serious drawbacks. The most obvious problem is the reliance of these procedures on a skilled person to make the cloud classification. Although this is a relatively straightforward task for a meteorologist, it is time consuming and not suitable for the operational system we are aiming towards. Related to this is the fact that each study based a daily estimate on a single image. This assumes that the clouds observed are either representative of the entire day or are the dominant cloud modes for the period. Due to the rapid movement and evolution of clouds, particularly those of convective type, assuming the former is unsafe. As for the latter, this could be true over tropical land areas where the convective regime has a definite diurnal peak (however, observational studies suggest that there is little

significant diurnal cycle in total precipitation ; eg. Gray and Jacobson, 1977). We would then have to further assume that rainfall occurs solely as a response to the diurnal heating cycle, and this is clearly not the case.

Enhancements of the basic method

Garcia (1985) later developed the results of Kilonsky and Ramage (1976) into the HRC Index. Due to the greater availability and ease of processing digital data, Garcia was able to overcome the once-daily sampling problem, and in fact extended the algorithm to include nighttime IR data. This index is frequently applied over the tropical ocean where rainfall is dominated by deep highly reflective clouds. A more recent and sophisticated multifeature classification approach is that of Grassotti & Garand (1994) who combined IR, Vis, and 6-hour numerical model forecast precipitation fields. They classified 1.25° grid boxes in the AIP-1 area using various selections of features calculated from IR, Vis, and model forecast field input. The features applied in the scheme included albedo (AL), cloud top pressure (CTP), cloud fraction (CF), and 6-hour forecast rain rate (RR6) from a global model. As well as using different combinations of input data, they also varied the number of allowed classes. Although these classes are not cloud types as such, this is still essentially an indexing method, each class being assigned a rain rate based on a regression relation with gauge-corrected radar ground truth. Using a 15 day training set of June AIP-1 data, they then verified hourly and monthly rain amounts using June and July/August data. They were able to achieve good results using only 2 (night) or 3 (day) features and 20 classes. In general it was found that by increasing the amount of information available to the classifier, better results were obtained. So, for example, addition of Vis data to IR-only schemes tended to improve both hourly and monthly estimates for both June and July/August.

Problems with the enhanced method

Despite the fact that the inclusion of model data to a combined Vis/IR classification improved estimates during June, it was actually found to degrade the hourly results for July/August. This degradation was thought to be as a result of a reduction in quality of the RR6 product due to a change in the climatic regime between June and July. It is known that in the study region around Japan, the rainfall from early to mid-summer is characterised by the so-called Baiu front. Precipitation is a mixture of stratiform and convective rain associated with synoptic and subsynoptic-scale disturbances. After the passage of the front sometime in June, the precipitation regime becomes more convective. The model is better able to resolve the well-organised vertical motions at synoptic scales predominant in the earlier month, and this could at least partially account for why the model forecast has a better impact in June. It was also suggested that the model may fail to resolve orographic rainfall which might have become more significant in July/August. It is not clear that this would make the model estimate worse relative to the independent satellite estimate since it is also noted that orographic precipitation would exhibit little, if any, signal in IR and Vis measurements. This is because the rainfall would originate in low clouds that have only low to moderate albedos. These results would seem to discourage the inclusion of even short-range, coarse resolution, model forecast fields as features in attempting to classify convective precipitation.

Indexing methods - discussion

All of these cloud indexing methods rely upon empirically established relationships

between cloud types and raingauge-measured precipitation. Once calibrated, these figures would remain fixed, and the scheme cannot take into account precipitation efficiences and other factors that affect the rainrate from a particular cloud type on a particular day. For example, in a rainfall study over Venezuela, Riehl (1973) found that cumulonimbi in a shearing flow produced much less precipitation than cumulonimbi in a uniform flow. In addition, no regard is taken of topographical or regional influences, and hence schemes calibrated in one location are not readily transferrable to other areas of the tropics. These methods may appear to give reasonable results much of the time, and in the right circumstances will, on occasion, do very well. However, due to the problems indicated, it is very unlikely that in their present form satisfactory results could be obtained on anything shorter than a monthly scale or smaller than several degrees of lat/long. Cloud indexing methods, although derived from the oldest of rain estimation techniques and still in use today, do not appear a great deal in current literature. This is especially true if we restrict our attention to the tropics, perhaps because in these regions much has been made of the univariate relationship between rainfall and cloud top temperature. There would seem to be scope for developing and applying classification methods like that of Grassotti & Garand (1994) to the tropics. The growing interest in neural networks and pattern recognition could represent the next stage of sophistication, replacing the more traditional classification techniques.

3.1.2. Thresholding

Principle, and initial results

The forerunner and best known of these methods originated with Arkin (1979). The goal was to develop an algorithm suitable for tropical rainfall estimation on a climatic scale. Arkin's method is based on relating the fractional coverage of cold cloud (FCCC) over an area to precipitation amount. 'Cold' cloud is that which has an equivalent black body temperature, calculated from the measured IR radiance, less than a specified threshold. Richards and Arkin (1981) considered a number of thresholds at a range of spatial (0.5°-2.5°) and temporal (1-24hrs) scales in calculating the FCCC. The data analysed suggested a linear relationship between rainfall amount and FCCC, and linear regressions between rainfall and FCCC were performed. As we would expect, they found better correlation with the rain amounts for larger spatial scales, and, to a lesser degree, for longer time scales. It was found that spatial estimates at 0.5° were of questionable value, but that there was no such lower limit on the time scale provided averaging was performed over a large enough area.

The GPI

Based on the previous work, Arkin and Meisner (1987) developed the GOES Precipitation Index (GPI) based on GOES IR data. They obtained FCCC using a threshold of 235K at a temporal averaging scale of one half month and a spatial scale of 2.5°. This fractional coverage was then converted to the precipitation index using the formula:

$$GPI = 3 * f * \Delta t \ mm$$

where the value 3 represents the slope of the regression line between rainrate and FCCC, f

is the FCCC, and Δt is the length of the period in hours over which f was the mean fractional cloudiness.

Drawbacks of simple thresholding methods

In its simplicity, the GPI, and other thresholding methods like it, can be inflexible. The assumption that all clouds colder than a certain threshold temperature precipitate, and those that are warmer do not, is clearly a gross approximation. The diagnosed rainfall area is generally exaggerated, partly due to the misinterpretation of high cold cirrus as precipitating cloud, and the method saturates whenever there is complete cold cloud coverage.

3.1.3. Bispectral techniques

Principle

In the context of rainfall estimation, bispectral techniques attempt to employ both Vis and IR information in combination. The assumption of IR thresholding techniques that cold clouds precipitate and warm clouds do not is a good one to make if dealing solely with cumulus cloud. However, cirrus cloud is high and cold, but often non-precipitating. Conversely, stratus cloud may appear warm in a scene, but often contributes a significant amount of rainfall. By including information on cloud thickness supplied by a Vis channel, bispectral techniques allow rainfall to be diagnosed from stratus cloud whilst at the same time moderating overestimates due to thin cirrus. Of course, an alternative means of estimating rainfall at night must be available to complement the daytime-only bispectral technique. Dittberner and Vonder Haar (1973) used a bispectral technique to study the Indian Summer Monsoon at large spatial scales. Rather than using a classification procedure, they based their precipitation estimate on deviation from the expected seasonal value using the formula:

$$P=c_1E+c_2A+P_0$$

where P is the percentage of normal seasonal precipitation, E is the seasonal mean infrared radiant exitance, A is the seasonal mean visible albedo, and the remaining parameters are regression coefficients. They found that this bispectral technique could differentiate between weak and intense monsoons, whereas a similar technique using only IR or Vis alone could not. This supports the view that useful additional information can be gleaned from incorporating Vis data.

The Lovejoy and Austin method

Lovejoy and Austin (1979a) attempted to delineate rain (> 0.5mm/h) and no-rain areas using radar data from Montreal (mid-latitude) and GATE (tropical) as ground truth to GOES IR and Vis data. They plotted 40km square pixel values of Vis and IR on a 2D feature space. They divided the total number of raining pixels by the total number of pixels at each location in the space to give the precipitation probability for each IR/Vis combination. By minimising a loss function they calculated a precipitation probability threshold at which to delineate rain areas. Statistical analysis implied that rain/no-rain categories did represent truly distinct, and therefore separable, populations. However, the same statistics demonstrated that light and heavy (> 2mm/h) rain could not be

distinguished as separate populations from their Vis and IR pixel values. They compared their results to the equivalent 1D method using only Vis or IR data, the classification boundary being a straight line. This 1D approach is in effect a thresholding technique. In all cases, they found the bispectral results to be superior to the monospectral, although the 1D Vis threshold was almost as good as the 2D optimum boundary for the GATE data. Lovejoy and Austin suggest that these results support those of Stout et. al. (1977), that Vis images give less error in rainfall amount estimation than IR images.

Transferrability

Lovejoy and Austin went on to attempt to produce an optimum boundary based on an aggregate of the statistics from a number of images over 11 GATE and Montreal days. They conclude that this boundary is relatively insensitive to diurnal and day-to-day variations, and yet it is very different for the tropical Atlantic and Montreal. It was also found to be significantly different over Montreal for convective and stratiform regimes. This would seem to imply that averaging statistics from times and places with differing characteristics would only serve to smear out the information detail, and could not lead to an improvement on the treatment of individual cases. This is a typical manifestation of the non-transferrability of the indirect methods. The authors conclude that useful operational rain maps could be supplied from this technique provided there is some radar coverage in the image area.

3.1.4. Life-history techniques

Background

Early work using Vis imagery brightness values from the Aplications Technology Satellites (ATS) as a key to estimating deep convective precipitation produced promising results. Sikdar (1972) observed sufficient correlation between brightness values and radar echoes, and between brightness values and rainfall to conclude that estimation of subsynoptic-scale convective precipitation was possible from geostationary data. Martin and Suomi (1972) proposed that deep convection could be isolated from surrounding cloudiness on the basis that very bright regions of ATS images related well to large radar echoes. Woodley and Sancho (1971) reached similar conclusions, and implemented the ideas in a rainfall estimation method (Woodley et al., 1972). They found good correspondence between brightness spots of ATS-3 imagery and radar echoes, and note that this correspondence is best for a young, vigorous cloud system, and worst for one which is old and decaying. This observation represents early experimental evidence of the importance of including life-history information in any attempt to derive rainfall from a brightness technique. As well as a source of supplementary information, observation of the evolution of a cloud can constitute the major or sole component of a retrieval.

The basic method

One such algorithm which relates convective rain rate solely to the life-cycle stage of a cumulonimbus cloud is that of Stout et al., (1979). Using SMS-1 imagery of an isolated thunderstorm, they delineated the cloud area using a threshold of 172 counts in the Vis and 160 counts (250K) in the IR. Although the area delineated in the Vis channel is generally somewhat smaller, the area evolution follows a very similar pattern in both channels. When compared to volumetric rain rate estimates derived from radar, it is apparent that the peak in areal extent of the cloud lags the peak in rain intensity by the

order of 1 or 2 hours. The rain rate is at its greatest when the cloud area is most rapidly expanding. These qualitative observations prompted the life-cycle stage of the cloud to be expressed in terms of the cloud area and time rate of change of area, and this is related simply to the volumetric rain rate by:

$$R = a_0 A + a_1 \frac{dA}{dt}$$

where R is volumetric rain rate (m^3s^{-1}), A is the cloud area (m^2), dA/dt the rate of change of area with time (m^2s^{-1}), and a_0 and a_1 are regression coefficients with dimensions ms^{-1} and m respectively. A least squares regression between half-hourly satellite-derived area information and radar-derived volumetric rain rate was performed to produce sets of coefficients for both the Vis and IR channels. The derived coefficients were then used to compare hourly images with radar data over the GATE area, resulting in a 0.84 correlation and a 0.25mm standard error of estimate.

Elaborations of the basic method

Griffith and Woodley (1975) developed an entirely automated life-history technique that has since been widely used in a number of slightly altered forms by a variety of investigators (Griffith et al., 1976; Woodley et al., 1980). Central to the scheme are a number of empirically-produced graphs which are used to infer an equivalent radar echo area from Vis or IR estimates of the cloud area. The scheme produces a precipitation estimate for each individual cloud, cloud being defined as anything colder than 253K, and as a preliminary step it is necessary to follow a cloud through its entire lifetime in order to calculate its maximum areal extent A_m. The equivalent radar echo area for any one image frame is then determined as a fraction of A_m depending on the current ratio A_c/A_m, where A_c is the current areal extent of the cloud, and on the sign of the time rate of change of A_c. The equivalent echo area is then converted to a rain rate by reference to a 2nd fixed graph. Finally, the actual volume of rainfall is calculated as the product of rain rate, echo area, the time interval between successive images, and an adjustment factor which increases the rainfall estimate as the cloud top temperature decreases. Half of this rainfall amount is attributed to the coldest 10% of the cloud, and half to the next coldest 40% of cloud top, with no rainfall being diagnosed from the warmest 50% of the cloud. The scheme was originally calibrated over Florida using Miami radar data. When applied to other areas of the globe, modifications to the way the rain is apportioned below the cloud and to the adjustment factor have been made although the original area-echo and echo-rainrate graphs have remained unchanged.

Problems and limitations

The major difficulty with this method is the need to track individual clouds throughout their life cyle. This is not possible using polar orbiters since the time between data samples is, at best, of the same magnitude as the lifetime of most convective clouds. While geostationary satellites do provide sufficiently frequent sampling to observe the life cycle of convective clouds, this cycle is often obscured by the interaction of the cirrus anvils of neighbouring clouds. In a region such as southern Florida there may be dozens of active thunderstorms in a summer afternoon, but by later in the day, after anvils have expanded and merged, perhaps only one entity is delineated by the 253K threshold. This

interaction of neighbouring cirrus anvils could in part account for why most Vis and IR precipitation schemes tend to underestimate convective precipitation early in the day and to overestimate it later. In the Griffith-Woodley algorithm, when clouds merge or split they are considered terminated and the resulting entities treated as new clouds. In an examination of the technique, Negri et. al. (1984) found that the merging and splitting actions were far too frequent for the life-history aspect to be meaningful. They proposed a simplified scheme which did not include cloud tracking, treating each image independently, and found that this performed no worse than the original algorithm. Griffith (1987a,b) also proposed a simplified scheme which does not track clouds and found that it too performed as well as the full Griffith-Woodley technique.

3.1.5. Cloud model techniques

In an attempt to rely less on empirically derived relationships, a cloud model may be used in a rain retrieval algorithm to incorporate information about the physical processes within a cloud.

Gruber's method

One of the first such attempts was by Gruber (1973a), who applied an element of Kuo's convection scheme (Kuo, 1965) to relate fractional cloud cover to rain rate. The scheme is based on a steady flow of moisture at a rate I into a grid box. If Q is the amount of moisture necessary to saturate the box, then I/Q is an estimate of the rate at which the box is filling with cloud. Next assume that all of the clouds within the box are convective and have lifetimes t_L, and suppose that the fractional cloud cover within the box is c. Then the rate at which cloud is diminishing is approximated by c/t_L. This leads to the equilibrium equation $I/Q=c/t_L$, and, since in Kuo's model all products of condensation are assumed to be immediately precipitated, we may replace I with R, where R is the area-averaged precipitation rate, to give $R=Qc/t_L$. Gruber was able to objectively evaluate t_L using data from the Experimental Meteorology Laboratory's cloud-seeding program in summer 1970. Q was calculated from special rawinsonde soundings, c and R from radar data, leaving t_L as the only unknown. Over a test period of 7 days the average value of t_L was found to be 31 minutes, with a range from 18 to 38 minutes. A subsequent application to independent data taking t_L = 30 minutes resulted in rainfall estimates within 50% of the value inferred from a sparse network of gauges (Gruber, 1973b). In this experiment Gruber chose his threshold for penetrative convection as the temperature level of zero buoyancy which was derived from a previous sounding.

Problems with Gruber's method

One potential difficulty with this method is the apparent need for sounding data to obtain both the temperature threshold and Q. However, we could assume a fixed threshold, and Gruber suggests that climatological values for Q may be sufficient since the variability of c was seen to be 3 or 4 times that of Q over the test cases. Other, more difficult, problems to remedy are those stemming from the use of Kuo's formulation. As an element of a parametrisation model, the method considers a population of clouds with a total c and an average value of t_L and therefore applies only to areas large compared to convective clouds. In addition, there are a number of assumptions implicit in Kuo's model which could lead to inaccuracies being passed on to Gruber's method. The model requires that there be a net moisture convergence over the grid box ie. that I is positive, and that there

is no inflow of unsaturated air. It also assumes a single depth of convective clouds. The use of a single value for t_L will lead to errors since in reality there will be an unpredictable distribution of cloud sizes and lifetimes. Krishnamurti (1968) observed that the cumulus scale vertical advection of momentum, the dynamical effects of downdrafts, and the microphysics of cloud production and dissipation are not included in the Kuo convective parameterisation.

Use of 1D models to adjust threshold and life-history results

Cloud models may be applied to rainfall estimation in other ways. For example, Wylie (1979) used the 1D model of Simpson and Wiggert (1969) as a means of calibrating techniques developed in the tropics for use in the extratropics. Although we are not concerned with the extratropics in this study, Wylie's procedure is worth considering in the broader context of the non-transferrability problem of empirical techniques. Essentially, a baseline rain rate is calculated for a 'control' area using an algorithm which has been calibrated with ground truth. The same algorithm is then used for the application area, and the rain rate adjusted to reflect the different environmental factors. Wylie used radar and satellite data from the GATE experiment. The volumetric rainfall was calculated from the radar and the cloud cover derived from the satellite data using a Vis or IR threshold. A mean uniform rain rate was then found by dividing the total rainfall by the total cloud cover. Similarly, a relationship between cloud cover and rain rate was derived for the Montreal area, but in this case it was found necessary to use different threshold values in order to obtain realistic cloud amounts. Soundings were taken at or near both areas, and those used as the input to the 1D cloud model. The rainfall estimate was then simply the product of the cloud area, the uniform rain rate calculated from the control, and the ratio of the 2 model precipitation outputs. The model precipitation products could not be used directly as they are based on simulating cloud growth by a single 'bubble ascent', when in reality a cloud system would be composed of many such 'bubbles'. Rather, the ratio of the model outputs acts as a scaling factor which takes account of the differing meteorological conditions from one area/time to another. Wylie used 2 days worth of GATE data as his control, and a single channel threshold delineating cloud as the basis of the rain estimate. This proved sufficient to demonstrate the feasibility of his idea, but there is no barrier to using sounding data and a cloud model with a more elaborate Vis/IR technique. Griffith et al. (1981) later used the same model in a similar way to adjust rainfall estimates over the semi-arid region of the US High Plains derived using the Griffith-Woodley life history technique. They conclude that by taking account of the differences between the region of estimation and the region in which the method was derived, useful rain estimates can be obtained for convective cloud in a non-tropical area.

The Convective Stratiform Technique

Adler and Negri (1988) used the cloud model results of Adler and Mack (1984) as a fundamental component of their Convective Stratiform Technique (CST). Adler and Mack were able to account for differences in the cloud height - rain relations (rain rate and rain volume) observed in summertime Florida and springtime Oklahoma by running a 1D cloud model with a variety of updraft radii for both areas. They found that variations in vertical velocity and precipitation efficiency dominate both the slopes of the Florida and Oklahoma cloud-rain curves and the differences between them. Adler and Negri's CST involves the isolation of convective cells by finding temperature minima in satellite IR imagery. Minima warmer than 253K are disregarded, and a check on the surrounding temperature

gradient is made to eliminate non-precipitating cirrus. The remaining minima are assumed to be convective cores. From the Florida model results of Adler and Mack they derived simple relationships between the minimum temperature of a convective core and its rain area and rain rate. The uniform rain rate is then assigned in an outward spiral from the identified core until the area limit is reached. This "inside-out" assignment differentiates the CST from most other techniques which rely on defining a relatively warm threshold, and then assigning rainfall to everything colder than this in an "outside-in" approach. The modal temperature of an area approximately 80km square centred on the convective element is assumed to represent the anvil temperature. The average of all the anvil temperatures is then considered a threshold for identifying the precipitating stratiform areas. These areas are assigned a uniform 2mm/h rain rate. In comparison to results from the GWT (Meitin et al., 1981), the NAWT (Negri et al., 1984), and a modified technique of Arkin (1979, 1983), the CST was found to provide a better estimate of 30 minute average rain amount over the FACE area. The technique also better represents the life cycle of thunderstorms, not having the same tendency to underestimate rainfall from younger systems and overestimate in the later stages due to misinterpretation of cirrus debris where the other algorithms suffer from their "outside-in" approach. The fact that the technique offers a reasonable breakdown of the total precipitation into convective and stratiform types (from mature and decaying anvils) could also be of great significance as the stratiform-type accounted for between 10 and 30% of the total rainfall in each of the study days. These stratiform estimates were significantly lower than the 40 to 50% calculated in a study by Houze and Rappaport (1984), and this difference could be indicative of regional differences.

Limitations of cloud-model techniques

With regard to implementation, the cloud model techniques all share the drawback of requiring a representative atmospheric sounding. Gruber suggests that climatological data could prove to be sufficient for his estimation, but it is unclear to what extent an approximation of this kind would affect results from the various model techniques over large space and time ranges. As an alternative to the use of sonde data, it may be possible to exploit the 3D fields of a numerical weather prediction model.

3.1.6. Summary - limitations of Vis and IR techniques

All of the algorithms discussed so far have been based on IR/Vis measurements of cloud tops. Since clouds are opaque at these wavelengths, precipitation cannot be sensed directly. Instead, the rainfall has to be inferred from measurement of the overlying cloud. For example, a number of studies have empirically related cloud top height to rainfall, (Wilk and Dooley, 1980; Konrad, 1977; Negri and Adler, 1981) and although strong correlations were found in each case, the curves describing the relationships vary considerably. The differences between the curves may be explained by the differing climatic regimes or even by the synoptic conditions prevalent at each of the study times. Although it is established that the probability of rainfall is greatest from bright, cold clouds, there is little correlation between the Vis brightness or IR temperature of a point and the rain rate beneath that point (Lovejoy and Austin, 1979b; Weiss and Smith, 1987). There is no universal relationship between rain and what is observable on the upper surface of the cloud. Thus these algorithms rely on a statistical relationship between cloud-top characteristics and precipitation. For example, there is a high correlation between a cloud's area and the total

volume of rain per unit time falling from it (Lovejoy and Austin, 1979b). Confirming this using radar data, Lopez et al. (1983) and Doneaud et al. (1984) have shown that the volume of rain that falls from a convective cloud through its lifetime is very nearly proportional to its time-integrated area. This means that if satellite data can define the raining area of a convective cloud, then the volumetric rainfall can be estimated (Doneaud et al., 1987); hence the success of many life-history techniques. Since Vis/IR techniques do not measure precipitation directly, we say that they are 'indirect'. Because of this, and often a lack of physical basis, the techniques are not readily transferrable to geographical locations outwith the area where they have been calibrated. Further, the algorithms tend to be tailored toward a particular space/time resolution. An algorithm which may give satisfactory monthly estimates on a 0.5° grid may not yield useful estimates of daily rainfall on a 2.5° grid. Averaging is necessary in order to reduce noise, but it is also inherently necessary for a statistical approach. There are also specific problems with techniques which can be alleviated by averaging. A cloud index-based estimate on an image may, for the individual clouds identified, include errors associated with the neglect of life-cycle effects. However, in averaging over large areas, or over a time sequence, many clouds at different stages of their life-cycle are identified and these errors cancel out. Similarly, thresholding techniques based on the association between cold-cloud and precipitation may miss warm-rain events whilst assigning a rainrate to non-precipitating cirrus. Over a sufficient time or space scale these errors will tend to cancel one another out. Thus, despite the existence of geostationary sensors which can provide frequent data at pixel resolutions of a few kilometres, precipitation estimates based on IR/Vis data are inherently limited in resolution by the nature of the retrieval algorithms.

3.2. Passive Microwave Techniques

Estimation of precipitation from space by observing upwelling microwave radiation has been feasible since the launch of the ESMR-5 instrument onboard Nimbus-5 in 1972. Further instruments such as the ESMR-6 and the SMMR followed, and in recent years the growing availability of data from the SSM/I has led to widespread research in using passive microwave signals to derive rain rates. The problem of retrieving information concerning the distribution and rate of rainfall from microwave measurements is very different from IR/Vis approaches. Unlike the shorter wavelengths, microwaves only weakly interact with cloud droplets. Thus, clouds are virtually transparent to microwaves, and a signal from any underlying precipitation can penetrate to the sensor. Hydrometeor-sized particles interact strongly with microwaves, the nature of the interaction varying with the frequency of the radiation and the type of particle involved. Since it is the effect of the precipitation itself on the microwave signal which is observed rather than the overlying cloud, it is often stated that microwave techniques are 'direct'. The physical link between microwave observations and precipitation is better understood than the largely empirical connection between precipitation and IR/Vis cloud characteristics, and this has resulted in microwave algorithms more often having a sound physical basis. Thus, microwave-based rainfall algorithms do not tend to suffer from the same calibration and transferability problems of their indirect counterparts. With microwave techniques it would be reasonable to expect better results from averaging over space and time, but this is not an essential part of the algorithm. Despite the quantifiable influence of precipitation on microwave radiation, the task of unambiguously assigning rain rates is not straightforward. Particularly in the last 10 years, with the growing interest in global precipitation and the

availability of multichannel dual-polarised SSM/I data, a great number of algorithms have been proposed, developed, and tested. There remains significant discrepancy both between these algorithms, and between the algorithms and ground truth.

Frequency dependence

By using a radiative transfer equation and making some assumptions about the rain characteristics and its atmospheric environment, it is possible to relate microwave radiance to rain rate. Of particular interest is the behaviour at frequencies corresponding to the channels of the SSM/I. The SSM/I is a seven channel, four frequency, linearly polarised instrument which is currently flown on the two sun-synchronous DMSP satellites F-13 and F-14. It measures horizontal and vertical polarisation components at 19, 37, and 85GHz, and vertical only at 22GHz (Hollinger et al. 1987). Liquid and ice hydrometeors are the most significant atmospheric constituents when considering microwave interactions. Although absorption dominates, liquid water can both absorb and scatter. In the case of ice, scattering is by far the dominant mechanism, so that the absorption component is insignificant. Scattering and absorption both increase with frequency and with rain rate, however scattering by ice increases much more rapidly with frequency than scattering by liquid. By applying Mie theory (Mie, 1908), it can be demonstrated that at frequencies below the water vapour line around 22GHz, it is the absorption of microwaves which is the dominant mechanism, and hence ice particles are virtually transparent. At frequencies beyond the oxygen complex at about 60GHz, it is the scattering regime which is of greatest importance, and therefore only the signal from ice crystals is observable. Between these frequencies the problem is more complicated, and either absorption or scattering can dominate (Spencer et al. 1989). Microwave algorithms can therefore be naturally divided into absorption/emission and scattering techniques.

3.2.1. The Absorption/Emission Approach

Basis of the method

Absorption/emission schemes are based on the absorption and corresponding emission (Kirchoff's law) of low frequency microwaves by liquid water. From a simplified radiative transfer equation, the brightness temperature radiance in the absence of rain is approximated by $T_B=\epsilon T_S$ where T_S is the thermodynamic surface temperature, and ϵ is the emissivity of the surface. As the rain rate increases, the brightness temperature converges to the temperature of the rain layer. This is what we might intuitively expect since, as the rain layer's transmittance decreases, the rain will obscure the surface while becoming increasingly visible itself. Over a cold ($\epsilon << 1$) background such as the ocean, the increase in T_B provides sufficient signal for rain rate retrieval. Now, rain rate is related to the volume absorption coefficient, whereas the radiance received at the sensor will be related to the product of the volume absorption coefficient and the depth of the rain layer. Hence, although the drop distribution is not important, all absorption-based techniques must make some assumption about the depth of the rain layer. Assumptions must also be made about the atmospheric environment, in particular about the distribution of other microwave absorbers such as cloud droplets (non-precipitating), water vapour, and oxygen. Despite these uncertainties, reasonable results can be obtained over the oceans.
Unfortunately, rain areas do not contrast well against the relatively warm (high emissivity) and inhomogeneous (variable emissivity) land surface. Variations in observed T_B due to the varying land surface are of the same magnitude as rain contributions and hence there

is no unambiguous signal for use in a retrieval. A further problem with these techniques is that at rain rates of around 20mm/h the method saturates. Once this threshold is reached, the brightness temperature will start to drop off slowly due to weak scattering by the liquid raindrops which reflect the cold cosmic background and reduce the emissivity of the now-opaque rain layer. This saturation threshold lowers with increasing frequency, and therefore it is the lowest available frequency which is favoured for rain estimation. Partial beam-filling can also lead to serious errors in retrievals due to the nonlinear relationship between brightness temperature and rain rate. It is often the case that the rain rate will be inhomogeneous across a sensor footprint which is several tens of kilometres. The pixel radiance will be an average value, and, for emission-based techniques, the rain rate will always be underestimated.

Implementations

An early example of an emission-based technique is that of Wilheit et al. (1977). This algorithm was originally developed to interpret over-ocean Nimbus-5 ESMR-5 observations at 19.35GHz. The basis of the algorithm lies in considering a simple atmospheric model containing a Marshall-Palmer distribution of raindrops (Marshall and Palmer 1948) between the ocean surface and the freezing level. Also assumed are a nonprecipitating cloud containing 0.25kgm^{-2} of integrated liquid water in the 0.5km below the freezing level, and a constant lapse rate of 6.5°Ckm^{-1}. The relative humidity is assumed to increase linearly with height from 80% at the ocean surface to 100% at the freezing level and above. Then, by using a radiative transfer equation and choosing a value for the freezing level, a relation between rain rate and brightness temperature can be derived. Observations were used to verify that the descriptions of the rain-T_B relationships were reasonable for both 19 and 37GHz with a 4km freezing level. Wilheit et al. (1991) later went on to modify and refine this algorithm for use with SSM/I data. Using channel differences they were able to reduce the impact of the variability of water vapour, and further used this information about the water vapour content of the atmosphere as a proxy for the freezing level height. As well as making improvements in establishing the rain rate - brightness temperature relation by reducing the number of assumptions, they also described the use of probability distribution functions to alleviate the sampling shortcomings of SSM/I for global estimates. The authors cite the lack of a beam-filling correction as the greatest shortcoming of the algorithm. Extrapolation of results by Chiu et al. (1989) suggest that the beam filling problem could lead to underestimates by a factor of 1.8 at SSM/I 19GHz. This correction factor was applied uniformly to all results from this algorithm for the AIP-3 study. Chang also submitted a version of the Wilheit algorithm to the AIP-3 (Ebert, 1996), the main distinction being the replacement of emission estimates by 85GHz scattering estimates when a strong scattering signal is present.

3.2.2. The Scattering Approach

Basis of the method

At microwave frequencies, radiation from the cold cosmic background is reflected by rain drops, and by ice crystals above a rain layer, resulting in an observed brightness temperature depression at the satellite sensor. The ice phase produces a particularly strong depression signal due to its high single scatter albedo and lack of compensating emission,

and this response increases rapidly with frequency. Volume scattering by hydrometeors is probably the most striking geophysical passive signature in the microwave spectrum, and can lead to temperature depressions of 200 degrees at 85GHz. An advantage over the absorption approach is that rainrate may be estimated over both land and sea. This versatility, and the ability to detect very high rain rates without saturating, has made scattering techniques the focus of much attention. However, since it is the signal from the ice phase rather than the precipitation itself which is measured, these techniques are necessarily more indirect than the emission-based type. The ice phase is closely involved in raindrop formation, and thus it would be unfair to say that these methods are as indirect as the IR/Vis techniques. Nevertheless, the scattering-based measurements must be calibrated empirically according to season and climatic regime. The brightness temperatures that are observed in the scattering regime depend on the many details of the ice layer such as particle sizes, shapes, and densities. These details are not important to the low-frequency (< 22GHz) algorithms, but are critical to the correct interpretation of scattering signals at high frequency. Even if we did have perfect knowledge of the characteristics of the ice phase, these parameters do not appear to be uniquely related to rainfall intensity (Wilheit et al. 1991). At 85GHz frequency, ice crystals must have achieved a diameter of around 0.3mm for a significant depression in the brightness temperature to be observed, and at 37GHz this increases to around 0.8mm. Clearly, warm rain events, where the drops form without an ice phase, will produce insufficient scattering for rain to be identified. Conversely, surface features such as snow cover, deserts, and sea ice may be incorrectly diagnosed as precipitation.

Implementations

One of the simplest types of microwave algorithm presented in the AIP-3 is based on the physical principle that high frequency microwaves will be scattered by precipitation-sized particles to a greater degree than will lower frequency microwaves. Kidd and Barrett (see Ebert, 1996) submitted the high-frequency vertically-polarised frequency difference algorithm which takes the form:

$$RR = 3.55 + 0.123[T_B(37V) - T_B(85V)]$$

where RR is the rain rate, and the T_B's are brightness temperatures given by the vertically polarised 37GHz and 85GHz channels. The calibration coefficients were empirically derived from 10 months of UK Met Office FRONTIERS radar products. Previous studies considered this algorithm over land (Grody, 1984; Barrett et al., 1988), but it can also be applied over oceans due to its high responsiveness to rain intensity. Some algorithms which are based on scattering at the 85GHz channel also exploit other channels of the SSM/I as a means of delimiting rain areas before assigning a rain rate. The Goddard Scattering Algorithm (GSCAT) of Adler is one such algorithm (Ebert, 1996), and is an extension of an approach first described in Adler et al., 1993. Rain rate relations were derived from a physical approach using a combined cloud/radiative transfer model (Adler et al., 1991), and are given by:

$$RR = [251.0 - T_B(85H)]/4.19$$

valid over land, where RR is rain rate in mmh^{-1}, and $T_B(85H)$ is the brightness temperature of the horizontally-polarised 85GHz channel. For retrievals over the ocean, the rain rate is given by:

$$RR=[251.0-T_B(85H)]/2.09$$

Grody (1991) developed a "scattering index" which, in common with the previous algorithms, is a measure of the T_B depression at 85GHz due to the presence of ice. Ferraro et al. (1994) revised the algorithm, and the scattering indices for over-land (SIL) and over-ocean (SIW) are given by the combinations of three channels:

$$SIL=438.5-0.46*T_B(19V)-1.735*T_B(22V)+0.00589*T_B(22V)^2-T_B(85V)$$

$$SIW=-174.4+0.715*T_B(19V)+2.439*T_B(22V)-0.00504*T_B(22V)^2-T_B(85V)$$

where the units of the indices are degrees Kelvin. If these indices equate to 10K or greater, then this is a good indication that rainfall is present, and rates can be calculated from the formulae:

$$RRL=0.00513*SIL^{1.9468}$$

$$RRW=0.00115*SIW^{2.16832}$$

To prevent the retrieval of unrealistically high rain rates, this algorithm includes a maximum cut-off check which assigns the value $35mmh^{-1}$ to any derived rate exceeding $35mmh^{-1}$. These algorithms represent just a very few of the many variants in existence, but give an idea of the form these take, whether derived from empirical studies or from "first-principle" calculations using cloud models and radiative transfer equations.

3.3. Combined microwave and Vis/IR techniques

Several researchers have suggested that combined techniques incorprating the coverage of a geostationary with the accuracy of microwave are the way forward (e.g., Adler et al., 1994). This would seem to be an attractive option, using the SSM/I somehow to calibrate or correct the indirect estimates. As descibed in section 2, Krishnamurti et al. (1995) used such an approach to 'sharpen' his estimates for assimilation into the FSU model. Several of the algorithms submitted to the AIP-3 for intercomparison were of this combined type. However, it should not be assumed that by including microwave data we are automatically going to achieve better results. Krishnamurti noted very different responses in the FSU

model when rain rates derived from the same IR data, but sharpened by three different microwave algorithms, were assimilated. The microwave-only algorithms of the AIP-3 appear similar as a group and superior to the Vis/IR techniques for instantaneous retrievals. The correlations for the microwave algorithms were in the range 0.60-0.78 compared with 0.43-0.58 for the geostationary, and appear to give a better spatial description of rainfall. However, we cannot have complete confidence in microwave retrievals since the rates derived from different microwave algorithms can be greatly different from one another. The results of the PIP-1 (Barrett et al. 1994) showed similar uncertainty in defining a best microwave algorithm when ten of these were intercompared. No one algorithm outperformed all of the others for all regions, and it was not obvious how these 'regions' were defined or why there were discrepancies. Quantification of a scattering signal is the only microwave approach which will work over land as well as ocean, and this requires empirical calibration in much the same way as a Vis/IR algorithm. With these reservations about the ability of current microwave algorithms, it is not surprising to find that the combined IR/microwave techniques of the AIP-3 appeared no better than the algorithms employing IR data alone. In order for a mixed IR-SSM/I algorithm to perform better than the IR-only algorithm incorporated within, it must be coupled with an SSM/I algorithm having a significantly smaller mean bias (Ebert, 1996).

4. The choice of algorithm

4.1. Algorithm comparison experiments

Although this brief discussion of the various approaches to rain retrieval from space has demonstrated the breadth of options, it leaves open the question of which approach best suits our needs. Table 2 provides a summary of most of the algorithms mentioned. Many of the algorithms date back a number of years, and have been included as representative examples of the pioneering work in the field. Although they have since been modified many times, the concepts on which they were based underlie much current work.

AIP-3

Ideally, all of the algorithms would have been verified in the same manner using a large data set representative of the tropical systems we wish to evaluate. In reality, most have been verified only on small datasets from limited regions of the globe and at varying degrees of spatial and temporal resolution. Thus, any statistics reported must be treated with caution and are not readily compared. This problem was directly addressed by the establishment of a series of Algorithm Intercomparison Projects by the GPCP. These projects attempted to make a rigorous evaluation of satellite rainfall estimation techniques, and to assess whether or not improvements could be made. The most recent of these was the AIP-3, which also happens to be the most relevant to this report as it dealt with a tropical regime. This was an international study which brought together over 50 algorithms submitted by various research institutions. All of the algorithms were evaluated on a common dataset derived from November 1992 to February 1993 over the TOGA COARE Intensive Flux Array area (Ebert, 1996). The study included geostationary IR/Vis algorithms, one based on AVHRR, passive microwave techniques, and "mixed" algorithms incorporating both geostationary IR and DMSP passive microwave data. It was found that most satellite algorithms overestimated the rain amounts by around 30% compared with

radar, and that no single technique was shown to be significantly better than the others. Background information and the complete results of this study are recorded in Ebert, 1996.

Comparison of selected algorithms from AIP-3

In an effort to interpret the results of AIP-3 and explain the differences found between techniques, four of the widely available algorithms were applied to two case studies (Ebert, 1996). Of these four, three were based on SSM/I data and the fourth on GMS IR. Although the microwave algorithms differed in their estimates of rain area, all showed greater ability than the IR algorithm to reproduce the spatial pattern of rainfall. It was hoped for some years prior to the intercomparison projects that the more direct and physically-based microwave approach would provide estimates of instantaneous rain rate superior to those derived using indirect Vis/IR measurements. This was demonstrated unambiguously during the AIP-1 (Lee et al. 1991), and was confirmed by the results of AIP-2 and AIP-3. The difficulty with these techniques is the poor sampling frequency of the SSM/I. From two DMSP satellites, total coverage of the tropics is barely achieved every 6 hours, and this coverage is not a snapshot but rather a mosaic of measurements with data spanning the entire 6 hour period (Krishnamurti et al. 1995).

Spatial and temporal variability

The high variablity of precipitation occurrence in space and time will lead to sampling errors if we try to extrapolate retrievals beyond the observed data. Better understanding of this variability would help to alleviate the problem by allowing the development of more realistic statistical distribution functions for rainfall. Although a number of studies have identified the existence of diurnal cycles for tropical convection over land and ocean (Houze and Betts, 1981), there remains significant uncertainty. A recent study by Weng et al. (1994), using one month of SSM/I data, reported high inter-daily variability which suggested the lack of a predictable diurnal cycle over land. The situation is complicated by findings from Hendon and Woodberry (1993) which show that stratiform rainfall over the tropical ocean exhibits a different diurnal cycle from that of convection. We cannot hope to discover more about the diurnal variations of tropical precipitation from the SSM/I alone since it is only flown on sun-synchronous satellites, and therefore always crosses the equator within the same narrow bands of local time in the morning and evening (although the satellite orbits do precess by around 30 minutes per year). In terms of spatial variability, Bellon and Austin (1986) estimated that the difference in the accumulated rainfall could be 100% for two rain gauges separated by 100km. Thus, in order to sample with sufficient resolution and coverage to capture the variability of precipitation across the tropics, we are compelled to use geostationary data. It is this great advantage which has maintained the widespread research interest in Vis/IR rain retrieval techniques despite the arrival of new microwave instruments.

4.2. Advantages and disadvatages of existing techniques

Since the weight of evidence suggests that there may be little improvement found by incorporating an SSM/I correction to an IR technique (see section 3.3), and since SSM/I alone cannot provide us with the coverage we require, it is proposed that a first approach be based on geostationary data. Taking this as the starting point will not prohibit later inclusion of SSM/I data, and it will provide a baseline against which to measure any subsequent improvement. As with SSM/I algorithms, no single IR technique can be said to

be better in all respects than any other. The choice of algorithm must be based on qualitative considerations such as "does the algorithm have any physical aspect to it?" and "does it rely on other inputs for its accuracy?" as well as quantitative verification if possible.

The CST

The Convective Stratiform Technique (CST) of Adler and Negri (1988) is perhaps the single most promising IR algorithm in the literature for obtaining estimates of precipitation (both convective and stratiform). It is a relatively new technique which continues to be developed, and as such can benefit from the lessons of past studies. Like the threshold techniques which have been successfully used in the tropics for years (eg. GPI), it is based on minima of cloud brightness temperature in the infrared, but does not suffer from many of their drawbacks. It is conceptually different because it identifies minima in a scene based on gradients rather than having a single critical fixed threshold temperature, and thus can be more generally applied with greater confidence and with less reliance on local and seasonal calibration. This gradient approach is very naturally able to include a check for non-precipitating cirrus. By its "inside-out" approach this technique is often more conservative in its delineation of rain area, and suffers less from the misdiagnosis of spreading anvils of decaying convective systems. As with other IR techniques, there must be some spatial and/or temporal averaging to obtain sensible results. Investigations using spatial scales from 32km to 128km by Adler and Negri (1988) led them to conclude that applying satellite IR rain estimates to scales below 100km (at one-half hour time resolution) will lead to unsatisfactory results. Accepting that there is some equivalence between spatial and temporal averaging, this limit is very close to our requirement for 3 hour averages at 60km. There is nothing in the current literature to suggest that any IR-based technique could provide estimates at better resolution than this.

Problems with implementing the CST

However, discussions with cloud modellers confirmed that there could be serious difficulties in applying the technique. One of these stems from the existence of empirical components in the CST. For example, the specification of the linear function to discriminate convective centres, the brightness correction applied to account for scale differences in the imagery, and the assignment of a $2mmh^{-1}$ stratiform rain rate are all empirically derived. However, of most concern is the way that rain area is derived from cloud top temperature. During the calibration phase, the cloud model is run a number of times using a representative atmospheric profile and with updraft parcels of various radii. The model shows that larger parcels rise higher and spread out over a larger area at the top of their ascent. By using a simple regression, Adler & Negri establish that the rain area is five times the updraft area. Thus, given a conversion between cloud top temperature and height, both rain area and rain amount can be inferred from satellite cloud temperature data alone. The appeal of applying physical precepts via a cloud model is somewhat weakened by this empirical assertion that the rain and updraft areas are related by a factor of five.

These results are peculiar to the model and profile used. For example, the Office's Single Column Model (SCM) cannot predict rain area. Similar experiments to those on which the CST is based would have to be performed to relate rain rate and area. Further, new scaling factors would have to be calculated to translate between the different horizontal resolutions

of the model updraft parcels and the various satellite instrument observations. Further, since the SCM only supplies cloud top to the nearest model level, errors in relating an observed temperature to a height would be exacerbated. A significant amount of work would have to be done to calibrate the technique for different regions and areas of the globe, and to define those regions and select appropriate profiles for each.

Not surprisingly, the rate of tropical convective rainfall will be sensitive to the moisture convergence in the area, and in using a 1D model we must somehow satisfactorily account for the surrounding environment. The suggestion has been made that a cloud resolving model might be a more appropriate tool to use for this work.

4.3. An initial approach

To avoid, at least to start with, the problems described in the previous section, it is suggested that studies should begin with a very simple algorithm which will allow an end to end system to be established quickly. Improvements to the method can then be tried in the light of the errors and deficiencies revealed. The option remains of eventually choosing a complicated method such as the CST, if initial results suggest that the effort would be justified.

In line with this approach, work is underway on comparing a global threshold product and UM convective precipitation analyses and forecasts. Model grid squares are 1.25° in the east/west direction, and 0.83° in the north/south. Rather than smoothing the higher resolution satellite data to this grid, satellite pixels are binned into their closest UM grid box. In this way, the temperature values of the IR data are preserved. The number of satellite pixels below the threshold value which fall within a grid box is normalised by the total number of pixels falling within the box, and this is then multiplied by a rate of $3mmh^{-1}$ in a similar way to the GPI product. Of the order of 100 pixels fall within each grid box, which should be a large enough sample to allow the uncertainties incurred in mismatches between the model and satellite grids to be ignored.

4.4. Possible enhancements of the initial scheme

If an improvement over the crude threshold technique described above is required, it is easiest to look for an option which is a natural extension of that technique. The CST is an entirely different approach, and cannot be used as a direct refinement of a threshold method.

Use of the UM to estimate the cloud-height/rain-rate relation

In discussions, it has been suggested that UM cloud and rain fields be compared as a means of calibrating the relationship between cloud height and rain rate. This has the attraction of a readily available dataset which is all on the same grid and can be compared immediately. However, we would need to derive a scaling factor to take account of the differing model and satellite resolutions. The relative ease of comparison of model fields should facilitate the selection of geographical and seasonal regimes, and the resulting relations between cloud height and rain rate would be consistent with the model's own climatology. Use of the UM to calibrate the rain rates reduces the potential of the satellite data to provide independent rain rate information, but this may not be a serious drawback

as it is believed that the value of the satellite data may lie more in its ability to correct rain areas in the UM than to provide accurate rates.

Incorporation of other satellite observations

The rain/no-rain mask of the threshold algorithm might be improved we by varying the threshold dynamically using information from another sensor such as the SSM/I. A rain algorithm could be applied to the nearest available SSM/I pass, and the threshold adjusted for optimum discrimination based on the IR values where the SSM/I indicates rain. This, together with the calibration from the model, would provide a relatively simple extension of the current comparison.

Pattern recognition techniques

Pattern recognition techniques have not been widely investigated or exploited in this application. In some sense all image-based techniques perform a basic kind of pattern recognition, but often using only one or two features as opposed to the wide range of shape, size, texture, and context features potentially available. If we wish to use more of the information contained in an image then we must find ways to take some of these additional features (local statistical descriptors) into account. Grassotti and Garand, 1994, was cited as one of the few references concerned with approaching the rainfall estimation problem in such a way. Although not applied so far to the tropics, recent work performed within the UK Met Office represents a more comprehensive treatment. 8 features from a possible 105 in AVHRR data were selected on the basis of their ability to distinguish rainfall classes, and the technique verified on extra-tropical cases using AIP-2 data (Pankiewicz, 1996). The greatest difficulty in establishing an algorithm suitable for the tropics would be the collection of suitable calibration information in the form of classified training data. Nevertheless, this kind of investigation may eventually offer the best way of inferring rainfall location and rates from indirect satellite observations.

5. Conclusion

Means of estimating tropical convective rainfall for assimilation into the global UM by "latent heat nudging" have been sought. A literature review has revealed a large number of algorithms, developed over the last two decades, for estimating precipitation from satellite observations. However all have limitations and none is clearly superior to the others.

The need to obtain frequent estimates, at night as well as in daylight, at all longitudes and using instruments currently available on operational satellites, has narrowed the choice to IR measurements from geostationary satellites, though there is the option of eventually using other sources, such as microwave imagers on polar orbiting satellites, to supplement and perhaps adjust the geostationary products.

An incremental approach has been proposed, starting with a very simple IR temperature threshold discriminator to establish an end-to-end system and assess the potential of the method and its deficiencies. Possible improvements to the inital method have been suggested. If, later, it is wished to adopt one of the published algorithms, the Convective Stratiform Technique of Adler and Negri (1988) appears to hold promise, though implementation would not be straightforward.

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GLOSSARY

AIP-1,2,3	First, second and third Algorithm Intercomparison Projects of the GPCP
AMEX	Australian Monsoon Experiment
ATS	Applications Technology Satellite
AVHRR	Advanced Very High Resolution Radiometer
CST	Convective Stratiform Technique
DA	Data Assimilation & Observation Processing
DMSP	Defense Meteorological Satellite Program
ECMWF	European Centre for Medium Range Weather Forecasting
EMEX	Equatorial Mesoscale Experiment
ESMR	Electrically Scanning Microwave Radiometer
ESSA	Environmental Science Service Administration
ETS	Equitable Threat Score
FACE	Florida Area Cumulus Experiment
FCCC	Fractional Coverage of Cold Cloud
FSU	Florida State University
GATE	Global Atlantic Tropical Experiment
GDAS	Global Data Assimilation System
GMS	Geostationary Meteorological Satellite
GOES	Geostationary Operational Environmental Satellite
GPCP	Global Precipitation Climatology Project
GPI	GOES Precipitation Index
GWT	Griffith-Woodley Technique
HIRS	High Resolution Infrared Radiation Sounder
HRC	Highly Reflective Cloud
IR	Infrared
LHN	Latent heat nudging
MG-GPI	Morrissey-Greene GPI
MRF	Medium Range Forecast
MW	Microwave
NAWT	Negri-Adler-Wetzel Technique
NCEP	National Center for Environmental Prediction
NESDIS	National Environmental Satellite, Data, and Information Service
NMC	National Meteorological Center
NOAA	National Oceanic & Atmospheric Administration
OLR	Outgoing Longwave Radiation
PIP	Precipitation Intercomparison Project
SCM	Single Column Model
SMMR	Scanning Multichannel Microwave Radiometer
SMS	Synchronous Meteorological Satellite
SSM/I	Special Sensor Microwave/Imager

STEP	Stratosphere-Troposphere Exchange Project
TIROS	Television & Infrared Observational Satellite
UM	Unified Model
UTC	Universal Co-ordinated Time
Vis	Visible

Table 1: Recent studies on the assimilation of precipitation

Model	Rainfall Algorithm	Data Source	Resolution	Assimilation Method	Reference
ECMWF	GPI	NOAA-HIRS	2.5° box 6 hours	non-linear normal mode initialisation scheme	Heckley et al. 1989
FSU	SSM/I-sharpened OLR	SSM/I and OLR(?)	100km 6 hours	physical initialization	Krishnamurti et al. 1995
NCEP T62	MG-GPI	Meteosat-3 Meteosat-4 GOES-7 and GMS	2.5° box 3 hours	physical initialization	Treadon 1995
NCEP T126	MG-GPI	Meteosat-5 GOES-7 and GMS	2.5° box 1 hour	physical initialization	Treadon 1996

Table 2: Satellite rain retrieval algorithms

Name	Inputs	Resolution	Thrust of approach	Notes	Reference
GPI	IR	2.5° 2 weeks	Statistical relationship between FCCC and rain amount 235K threshold R=3*FCCC*T mm	Could be applied at higher resolutions, see Jobard & Desbois (1992) for discussion of time & space averaging. Requires local calibration, see for example Morrissey & Greene (1993) for a bias correction. 5-day 2.5° totals produced operationally for GPCP.	Arkin & Meisner 1987
SSM/I-sharpened OLR	OLR (?) and SSM/I for calibration and raingauge	100km daily	Regression relation between Laplacian of SSM/I & OLR derived rain rates found from a database. Relation used to sharpen OLR estimates.	Gauge data necessary for merging sharpened OLR with SSM/I and gauge data. The sharpened OLR could be used as the final estimate. There are a number of things I am not clear on.	Gairola & Krishnamurti 1992
MG-GPI	as GPI	as GPI	as GPI	Noncontiguous raingauge (NCR) technique developed as a calibration tool. Slope & intercept correction factors to GPI relationship based on Pacific atoll gauge data using the NCR.	Morrissey & Greene 1993

Name	Inputs	Resolution	Thrust of approach	Notes	Reference
HRC Index	Vis (day) IR (night)	1° monthly	HRC defined as the number of deep, organised tropical convective systems extending at least 200km horizontally occurring in a 1° box; related to rainfall by the statistical relationship: R=39.2HRC + 55.3 mm/month	Requires subjective assessment of images to identify highly reflective clouds.	Garcia 1985
GG Multifeature	Best results with IR+Vis or IR+Vis+model forecast precipitation	1.25° hourly and monthly estimates	Variable number of features such as cloud fraction, albedo, cloud top pressure, model forecast rainrate used to partition image into up to 30 cloud/rain classes. Supervised training on a 15 day subset of the 2 month AIP-1 verification dataset.	Global model data found to degrade the hourly satellite estimates during a convective regime.	Grassotti & Garand 1994

Name	Inputs	Resolution	Thrust of approach	Notes	Reference
RACC	IR + SSM/I for learning phase IR for application	15-120km square 1-12 hours	Unsupervised classification into a number of rainfall categories (9) using IR pixel, IR variance (standard deviation of 3*3 square), and 86GHz scattering as features. IR features only for the application phase Best results obtained by learning a single set of classes over a long time period (say a month) rather than re-training more frequently	Trained over continental tropical Africa using EPSAT-NIGER gauge data. Easily trained for other regions/seasons provided verification data is available. May be better to use other MW frequencies over oceans. Decent results reported at 60km & 3 hour resolution ; outperformed simple threshold method. Possible non-independence of training/verification data contributed to good results.	Jobard & Desbois 1994
LA delineation	IR + Vis	40km half-hourly	Straight 2D classification into rain/no-rain points using Vis and IR as the feature space axes. Separate boundaries derived for GATE and Montreal using radar ground truth.	The 2 boundaries are relatively insensitive to diurnal and day-to-day variations, but are different for the 2 study areas. Light/heavy rain could not be identified as separate populations. Conclude that optimization by radar in real-time would allow operational production of useful rain maps.	Lovejoy & Austin 1979a

Name	Inputs	Resolution	Thrust of approach	Notes	Reference
Wylie	Vis or IR	200km radius (could be smaller) 3 hours	Basically a threshold method with a scaling factor applied to the rain rate derived from the input of sonde data to a 1D cloud model.	Accounts for differing cloud environments, but does require a nearby sonde ascent. Author suggests accuracy to within a factor of 2 for 3-hour accumulations.	Wylie 1979
GWT	Vis or IR	100km 6 hours (could be finer)	Life-history. Fixed empirical curves relate radar echo area, A_e, to cloud area defined by a simple threshold, A_c. Echo area then converted to rain volume by the linear relationship $R_v=IA_e$. I is empirically derived for different regions and for different echo growth criteria (eg. area increasing/decreasing). Algorithm applies to individual clouds.	The maximum extent of the cloud area, A_m, is required in advance to normalise the values of A_e & A_c. Following a cloud throughout its lifetime allows for more accurate results & better identification of precipitating cloud. Any cloud size of any lifespan can be considered. Precipitating area for calibration defined by 1mm/h threshold of gauge-corrected radar. Mean absolute error factors of less than 2 calculated for given resolution. Merging, splitting, & obscurement by stratiform cloud have all caused problems for researchers attempting to employ this method.	Woodley et al. 1980

Name	Inputs	Resolution	Thrust of approach	Notes	Reference
NAWT	IR	$1.3*10^4$ km^2 (FACE area) daily (or at resolution of time sampling & cloud size)	A much simplified GWT with no aspect of life history. Essentially a threshold method using 2 IR thresholds which vary with cloud size. Rain assigned to these delineated areas at 2 uniform rates.	Clouds defined by 253K isotherm. Investigation using a case study revealed the correlation between cloud area and rain volume to be of greatest contribution to a GWT estimate. Correlations between satellite and ground truth for 1/2 hourly estimates found to be poor for both GWT & NAWT.	Negri et al. 1984

Name	Inputs	Resolution	Thrust of approach	Notes	Reference
CST	IR	100km 6 hours (could be finer in time)	Minima in T_B field assigned rain areas & rates using results from previous 1D cloud model experiments. A uniform stratiform rain rate also assigned based on a threshold given by the anvil modal temperature in the current imagery.	Best results found for young, isolated storms. Not so good at picking out linear features such as squall lines. Slope parameter check to eliminate thin cirrus. "Inside-out" approach attempts to reduce early underestimation & late overestimation for convective systems. Verified on 4 cases during FACE-2. Stratiform component found to account for 10-30% of total rainfall. An empirical correction to the GOES T_{min} is necessary to resolve the scale difference between the imagery & the 1D cloud model (8km & 1km respectively). This correction is based on previous AVHRR comparisons. On a limited sample, found to produce better results than 3 other satellite techniques (GWT, NAWT, & GPI-type).	Adler & Negri 1988

Name	Inputs	Resolution	Thrust of approach	Notes	Reference
WWC	IR or IR+Vis	20km (13-100 pixels) each image	Pattern recognition technique using a subset of 48 radiance & texture features in IR & Vis imagery. Image classification into no rain, light rain, & heavy rain categories.	Training/verification data includes tropical storms & cyclones in Gulf of Mexico & S. Florida areas. Discriminating feature means of classes found to shift in time & with storm system. No simple threshold could be found to separate each class for all cases. Much improvement found on including texture features in addition to radiance features. High spatial resolution found to be important for texture features. Classification into 3 classes achieved with skill score of around 66%.	Wu et al. 1985